



Comparison Analysis and Application of GlobeLand30 and CNLUCC Datasets in Land Use Dynamic Analysis in Dongguan City

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Abstract— Accurate analysis of land use dynamics is fundamental for sustainable development and refined territorial spatial management in high-density urban areas. Although the GlobeLand30 and CNLUCC datasets have been widely used in land use studies, they fundamentally differ in classification systems, design objectives, and accuracy, and there remains a lack of systematic performance comparison and applicability assessment for highly dynamic urban areas. This study takes Dongguan City (2000–2020) as a case study, employing dynamic degree models, transition matrices, and spatial analysis methods to systematically compare the performance differences between the two datasets across three dimensions: classification system compatibility, spatiotemporal consistency, and application scenario suitability. The findings reveal that CNLUCC, with its management-oriented three-tier classification system, excels in identifying industrial land (accuracy up to 92%) and is suitable for localized fine-scale management scenarios such as territorial spatial planning. In contrast, GlobeLand30, with its globally consistent observation standards, achieves higher overall accuracy (85.72%) and proves particularly valuable for global change studies and cross-border comparisons. Based on the more accurate GlobeLand30 data analysis, Dongguan's land use exhibits a typical urbanization pattern characterized by "spatial polarization—boundary expansion—functional restructuring," with concurrent expansion of construction land and restoration of ecological land. Therefore, CNLUCC is recommended for territorial management, while GlobeLand30 is preferred for cross-border studies, and a hybrid validation strategy can be adopted for critical land category analyses. The comparative framework developed in this study provides a scientific basis for selecting land use data and guiding sustainable planning in similar high-density urban areas worldwide.



Keywords— CNLUCC (China Land Use/Land Cover Change); Globeland30; Land Use/Land Cover Change (LUCC) ; Dynamic Degree Analysis; Transfer Matrix

I. INTRODUCTION

Land Use/Land Cover Change (LUCC) research is a crucial component of global environmental change studies. Its data, serving as a spatial representation of the interaction between human activities and the natural environment, provides fundamental information for understanding human-land relationships. High-quality land use data can accurately reflect the spatiotemporal characteristics of surface cover changes, revealing the extent and methods of human interventions in natural systems—such as urbanization, agricultural development, and ecological restoration—thereby offering decision-making support for regional sustainable development. Particularly in rapidly urbanizing regions like the Pearl River Delta (PRD), where human-land conflicts are prominent, accurately identifying land use dynamics holds significant practical importance for optimizing territorial spatial patterns, ensuring ecological security, and improving resource utilization efficiency [1].

As a forefront of China's reform and opening-up and a vital engine for economic development, the PRD region has undergone rapid urbanization. Dongguan, as a core city in the PRD, has experienced particularly dramatic land use transformations over the past two decades. Between 2000 and 2020, Dongguan's urbanization rate surged from 40% to 92%, while the proportion of construction land increased from 15% to 45%. Meanwhile, the area of cropland decreased by 60%, intensifying the conflict between cropland loss and construction land expansion. Such drastic changes not only exert pressure on the regional ecological environment but also pose severe challenges to the sustainable utilization of land resources.

Remote sensing technology, with its advantages of macroscopic, rapid, and periodic observation, has become the primary means of obtaining large-scale, long-term land use information. Currently, with the conceptualization and practical application of remote sensing big data, land use data widely used in academic research includes global standardized datasets (such as GlobeLand30) and national or regional datasets (such as China's CNLUCC). Among them, the GlobeLand30 dataset is a global 30-meter resolution land cover dataset, representing a significant achievement of China's National High-Tech Research and Development Program (863 Program) on global land cover remote sensing mapping and key technology research. It

adopts a single-layer observational framework with 10 first-level categories, directly mapping based on physical land cover characteristics to ensure global-scale consistency. On the other hand, CNLUCC (China Multi-Period Land Use Remote Sensing Monitoring Dataset) primarily uses Landsat remote sensing imagery from the United States as its main data source. It employs a three-tier hierarchical management framework (6 first-level categories → 15 second-level categories → 30 third-level categories), with progressive subdivision based on land use control logic, making it more aligned with China's land management practices.

In recent years, these two datasets have been widely used in academic research, but each exhibits distinct strengths and limitations. In the academic community, GlobeLand30 has garnered broader attention and application due to its global coverage and consistent data standards, particularly in fields such as global change research and cross-border comparative analysis. Multiple studies indicate that GlobeLand30's overall accuracy typically exceeds 80% and continues to improve with version updates (the V2020 version achieved an overall accuracy of 85.72% with a Kappa coefficient of 0.82). On the other hand, the CNLUCC dataset is more widely utilized in domestic academic circles, demonstrating clear advantages in areas closely tied to national policies, such as territorial spatial planning, ecological conservation and restoration, and resource management. However, its accuracy shows some variability across different regions and application scenarios (with an overall accuracy of approximately 76.41%).

However, these two datasets exhibit significant differences in classification systems, spatial resolution, update frequency, and accuracy, directly impacting the reliability of land-use change analysis and the effectiveness of subsequent policies. Particularly in high-density urban areas like Dongguan, where land-use structures are complex and changes are rapid, different datasets may yield divergent conclusions about the same phenomenon. For instance, in Dongguan's case, CNLUCC achieved a 92% accuracy in identifying industrial land, whereas GlobeLand30 missed detecting 61.4% of wetlands. Such discrepancies create confusion for researchers when selecting data and compromise the comparability and

reliability of research findings.

Therefore, this study focuses on two datasets, CNLUCC and GlobeLand30, and quantitatively evaluates their performance in analyzing land use changes in Dongguan City from three dimensions: classification system, spatiotemporal consistency, and application scenario matching. By combining dynamic degree models and transition matrices, the study aims to clarify their respective advantages and limitations, providing a basis for data selection and result interpretation in related research.

II. STUDY AREA AND DATA

2.1 Overview of the Study Area

Dongguan City is located on the eastern bank of the Pearl River Estuary in the central-southern part of Guangdong Province (longitude 113°31' ~ 114°15'E, latitude 22°39' ~ 23°09'N) (Figure 1). As a key node city in the Guangdong-Hong Kong-Macao Greater Bay Area, it covers an area of 2,460.08 square kilometers. As a typical representative of high-density cities in the Pearl River Delta, its urbanization process and land use patterns exhibit rapid, intensive, and highly dynamic characteristics. By 2020, Dongguan's urbanization rate had reached 92%, with a permanent population of approximately 10.437 million. In 2024, its GDP amounted to 1,290.018 billion yuan, showcasing a developed economy dominated by manufacturing, a young population structure, and a low level of aging [2].

In terms of land use, Dongguan has undergone a dramatic transformation process. Between 2000 and 2020, the proportion of construction land surged from 15% to 45%, while farmland area decreased by 60%. The conflict between farmland loss and construction land expansion is prominent, reflecting the strong occupation of land resources by rapid urbanization. Currently, Dongguan has entered a new development phase centered on "stock renewal and connotation enhancement," completely shifting away from the traditional model of relying on new land supply and blind expansion. Instead, it focuses on tapping spatial potential through urban village redevelopment, industrial park upgrades, and the redevelopment of inefficient land use. The 2025 land supply plan clearly reflects this policy direction, with industrial and mining

storage land becoming the absolute dominant supply category (266.13 hectares, accounting for 55.93%), while residential land supply accounts for only 9.3% of the total annual supply (approximately 441,000 square meters). This highlights Dongguan's strong intent to safeguard manufacturing space and promote the integration of industry and urban development.

In terms of policy, according to the "Dongguan Territorial Spatial Master Plan (2021-2035)," the city's urban development boundary area is strictly controlled within 1,433.37 square kilometers, with increasingly refined land use management. By 2035, the plan aims to maintain a cultivated land area of no less than 101,100 mu and a permanent basic farmland protection area of no less than 100,000 mu, strengthening protection through the "Field Chief System" and the construction of cultivated land aggregation zones. The ecological protection redline area will be no less than 361.08 square kilometers (including a marine ecological protection redline of 26.74 square kilometers), focusing on protecting the ecological barrier in the southeastern mountainous areas and the wetland system of the Dongjiang River basin, while systematically advancing ecological restoration projects [3].

Topographically, Dongguan City generally presents a pattern of higher elevation in the southeast and lower in the northwest. The southeastern part is dominated by low mountains and hills (accounting for 44.5% of the city's land area), with the main peak of Yinpingzui Mountain reaching an altitude of 898.2 meters. The northwestern part consists of the alluvial plain of the Dongjiang River (43.3% of the land area), characterized by flat terrain and a crisscrossing network of waterways. The southwestern part belongs to the river alluvial plain, significantly influenced by tidal movements. This interlaced geographical pattern of "hills-plains-water bodies" has profoundly shaped the spatial differentiation of land use: ecological conservation is prioritized in the southeastern mountainous areas, while urban and agricultural development is concentrated in the northwestern plains. Dongguan is currently employing multiple approaches, including territorial spatial planning, urban renewal, and comprehensive land remediation, to reconcile land-use conflicts and optimize spatial structure, making it a typical case study for achieving high-quality development alongside high-level resource protection.

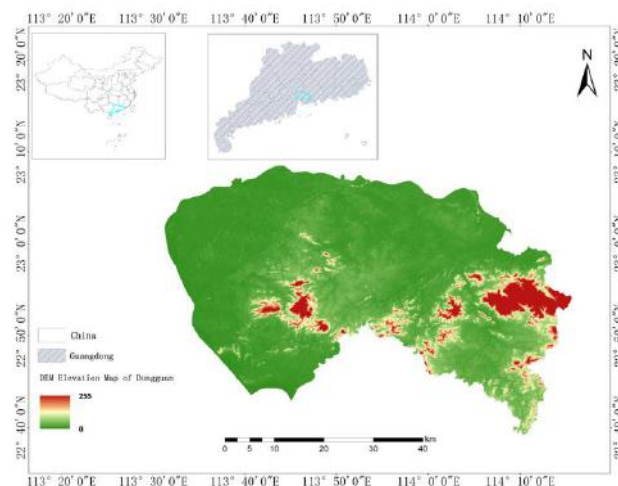


Fig.1 Location and Elevation Map of Dongguan

2.2 Data Sources and Preprocessing

2.2.1 Data Sources

The data for this study primarily comes from the global land cover dataset (GlobeLand30), the China Multi-period

Land Use Remote Sensing Monitoring Dataset (CNLUCC dataset) [3], and the Geospatial Data Cloud (Table 1). Three periods of remote sensing images for Dongguan City in 2000, 2010, and 2020 were selected, with both datasets having a spatial resolution of 30 m.

Table 1 Data Sources of This Study

Data Category	Data Sources	Purpose
Land use data	Chinese Academy of Sciences Resources and Environment Science Data Center (CNLUCC) https://www.resdc.cn/DOI/DOI.aspx?DOIID=54	Generate land uses dynamic degrees and transfer matrix data
	GlobeLand30 Global Land Cover Data http://www.globallandcover.com/	
DEM	Geospatial Data Cloud https://www.gscloud.cn/search	Generate elevation map of Dongguan City
Administrative Boundary (Vector Data)	National Platform for Common GeoSpatial Information Services https://www.tianditu.gov.cn/	Generate the study area boundary map

2.2.2 Data Preprocessing

This study utilized ArcGIS 10.4 software to preprocess and analyze GlobeLand30, CNLUCC, and Landsat remote sensing images, primarily for extracting spatiotemporal information on land use changes in Dongguan City. The specific workflow is as follows:

(1) Due to the diversity of data sources, their coordinate systems and pixel sizes are inconsistent.

Therefore, the Extract by Mask tool in the Spatial Analyst Tools was used to mask the data according to the study area. Additionally, the Define Projection and Project tools in the Data Management Toolbox were employed to unify all data to the geographic coordinate system WGS_1984 and the projected coordinate system WGS_1984_World_Mercator, while also standardizing pixel sizes to ensure spatial consistency.

(2) The original images underwent preprocessing, including background value removal and image mosaicking. The vector boundary of Dongguan City was then used for mask extraction to obtain land use data within the study area.

(3) ArcGIS was utilized for geometric calculations to generate a land use transfer matrix. The "Table to Excel" tool was employed to export the data, and the area of each land type during different periods, as well as the land use dynamic degree, were calculated.

III. RESEARCH METHODOLOGY

This study focuses on general data sources such as GlobeLand30 and CNLUCC. Through land use dynamic degree analysis (DDA), transfer matrix calculation, and classification accuracy assessment, it explores the appropriateness and precision of land use in the study area. By comparison, the study aims to scientifically evaluate the rationality, feasibility, and differences of the research data (Figure 2).

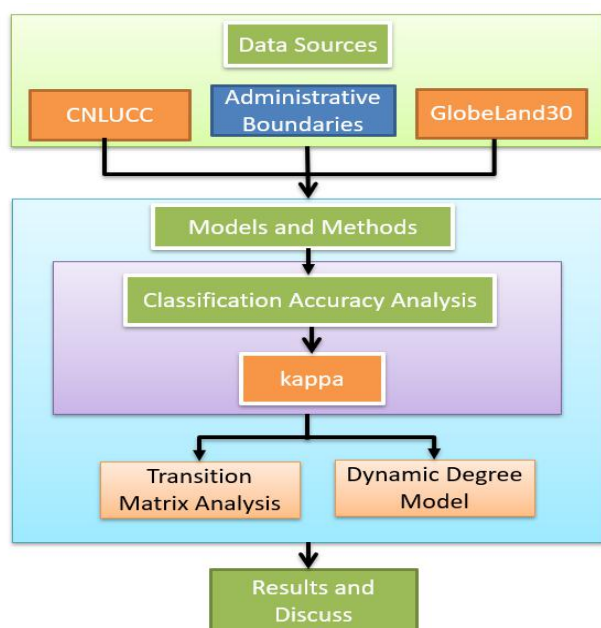


Fig.2 Technical Flowchart

3.1 Analysis of Land Use Dynamic Degree

3.1.1 Single Land Use Dynamic Degree

The single land use of dynamic degree refers to the rate of change in the area of a specific type of land use over a certain period. It reflects the dynamic changes of that type

of land use during the study period and is one of the important indicators for analyzing land use changes [4]. The formula is as follows:

$$K = \frac{A_m - A_n}{A_n} \times \frac{1}{T} \times 100\% \quad (1)$$

In Equation (1): K represents the single dynamic degree; A_n and A_m denote the area of a certain land use type at the beginning and end of the study period, respectively; T is the duration of the study period.

3.1.2 Comprehensive Land Use Dynamic Degree

The comprehensive land use dynamic degree refers to the overall changes in all land use types within a study area over a certain period. It reflects the general trend of land use change in the region [4]. The formula is as follows:

$$R = \frac{\sum_{i=1}^n |A_i - A_j|}{\sum_{i=1}^n A_i} \times \frac{1}{T} \times 100\% \quad (2)$$

In Equation (2): R is the comprehensive dynamic degree; A_i and A_j are the areas of the i-th land use type at the beginning and end of the study period, respectively; n is the number of land use types; and T is the duration of the study period.

3.2 Calculation Method of Land Use Transfer Matrix

The land use transfer matrix quantitatively describes the sources, destinations, areas, and rates of mutual conversion among various land use types during a study period by comparing land use data at two different time points (e.g., T1 and T2). Its core principle is based on the concept of Markov chains, where the future distribution of a system's state (land use types) depends only on its current state, and transitions between states can be described by a probability matrix (i.e., the transfer matrix). In summary, the land use transfer matrix is applied in system analysis to quantitatively describe system states and state transitions, encompassing both static data of land use types and dynamic data of mutual conversions among land categories within a specific region during a given period [5].

$$S_{ij} = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix} \quad (3)$$

In equation (3), where S is the area, n is the number of land use types before and after the transfer, i is the land use type before the transfer, and j is the land use type after the transfer, S_{ij} is the area of land type i that I converted to land type j , and each row element in the matrix represents the source information of each land type before the transfer for land type j .

Using the transfer matrix, the proportion of land use type i in period k converted to land use type j in period $k+1$ is calculated, as shown in formula (4):

$$A_{ij} = S_{ij} \times 100 / \sum_{j=1}^n S_{ij} \quad (4)$$

It can also calculate the proportion of land use type i in period k that transitions to land use type j in period $k+1$, as shown in formula (5):

$$B_{ij} = S_{ij} \times 100 / \sum_{j=1}^n S_{ij} \quad (5)$$

The application of land use transition matrices is extremely extensive, serving as a bridge connecting data with decision-making. Common research areas include (1) quantifying change processes and identifying characteristics (identifying dominant change types, revealing hotspot pathways of change, and analyzing the reversibility of changes); (2) analyzing driving mechanisms; (3) evaluating sustainable land use; (4) simulating and predicting future scenarios; and (5) assessing policies and testing their effectiveness.

3.3 Evaluation Metrics

To assess the stability and effectiveness of classification methods, scientific rigor, rationality, and accuracy serve as the core criteria for precision evaluation, providing indispensable reference value for method optimization and enhancement [6]. Research literature indicates that when analyzing experimental results, comparing the inherent differences between multi-class and

binary classification problems reveals that Overall Accuracy (OA) offers high precision in evaluating multi-class problems. In contrast, this metric struggles to comprehensively reflect the training efficacy of models for binary classification. Therefore, in land-use classification assessments, employing both OA and the Kappa coefficient for analysis can enhance reliability and credibility. Accordingly, this study adopts OA and the Kappa coefficient as key metrics to measure the precision of classification outcomes. The results of various classification models used in the experiments are compared with those of conventional models to validate the practical performance of the proposed method.

3.3.1 Overall Classification Accuracy

In classification methods, overall classification accuracy serves as an intuitive evaluation metric. It quantifies analysis by calculating the ratio of correctly predicted samples to the total number of samples (reflecting the proportion of samples that are accurately classified). The basic calculation formula is as follows:

$$OA = \text{Correct samples} / \text{Total samples} \quad (6)$$

Comprehensive classification accuracy is suitable for performing sample classification tasks involving multiple categories, during which the distribution of sample quantities across various categories should remain relatively balanced.

3.3.2 Kappa Coefficient

The Kappa coefficient is a crucial metric in land use classification, remote sensing image interpretation, and any scenario involving the evaluation of classification model accuracy. It is also an assessment indicator that integrates Producer's Accuracy and User's Accuracy. Widely applied in verifying the consistency between model-predicted data and actual monitoring data, it is frequently used in research to quantify the overall accuracy of simulated images. Its calculation is based on the confusion matrix, with the formula as follows:

$$Kappa = \frac{P_a - P_b}{1 - P} \quad (7)$$

In the formula, P_a represents the actual raster simulation accuracy, which is the overall accuracy (Total

Accuracy). As mentioned earlier, $TA = \text{number of correct samples} / \text{total number of samples}$; P_b refers to the expected raster simulation accuracy, while 1 symbolizes the simulation accuracy under ideal conditions. The Kappa coefficient ranges from [0, 1], and an increase in this value indicates an improvement in simulation accuracy. When Kappa is below 0.75, it suggests significant deviations in the simulation results; conversely, when Kappa is above 0.75, it implies a high consistency between the simulated image and the real landscape, indicating superior simulation quality.

IV. RESULTS AND ANALYSIS

4.1 Dataset Discrepancy Analysis

GlobeLand30 adopts a single-layer observational framework (10 parallel categories) (Table 2), directly mapping based on physical land cover characteristics to

ensure global consistency (e.g., uniform criteria for "built-up land 80"). However, this approach resulted in a 61.4% omission rate for wetlands in Dongguan. Essentially, the two datasets are products of distinct paradigms: "land resource management" (CNLUCC) and "surface process observation" (GlobeLand30), tailored respectively for territorial spatial planning (CNLUCC) and global change research (GlobeLand30) scenarios.

CNLUCC employs a three-tiered management framework (6 primary categories, 15 secondary categories, and 30 tertiary categories) (Table 3), hierarchically subdividing land use types based on regulatory logic. It supports refined governance through specialized classifications like "industrial/mining/warehouse land (203)," achieving a 92% industrial land detection rate in Dongguan. However, its cross-country comparability is limited.

Table 2 Classification System of GlobeLand30 Dataset

Code	Land Type	Content
10	Cropland	Land used for growing crops, including paddy fields, irrigated dry land, rain-fed dry land, vegetable fields, pastureland, greenhouse land, and cash cropland.
20	Forest land	Woodland with tree canopy coverage exceeding 30%, including deciduous broadleaf forests, evergreen broadleaf forests, deciduous coniferous forests, evergreen coniferous forests, mixed forests, as well as sparse woodlands with canopy coverage between 10% and 30%.
30	Grassland	Land naturally covered by herbaceous vegetation with a coverage rate of over 10%, including grasslands, meadows, savannas, desert steppes, and urban artificial lawns.
40	Shrubland	Shrub-covered land with a shrub coverage of more than 30%, including mountain shrubs, deciduous and evergreen shrubs, as well as desert shrubs with a coverage of more than 10% in desert areas.
50	Wetland	Located at the interface between land and water, wetlands are areas with shallow accumulations of water or waterlogged soil, typically supporting the growth of marsh or aquatic plants. .
60	Water body	Land areas covered by liquid water, including rivers, lakes, reservoirs, ponds, etc.
70	Tundra	Land covered by lichens, mosses, perennial cold-resistant herbs, and shrub vegetation in frigid and alpine environments, including shrub tundra, grass tundra, wet tundra, alpine tundra, and bare tundra.
80	Construction land	A surface formed by human construction activities, including various types of settlements such as towns, industrial and mining areas, transportation facilities, etc., excluding contiguous green spaces and water bodies within construction sites.
90	Bare land	Natural land with vegetation coverage below 10%, including deserts, sandy areas, gravel lands, bare rocks, saline-alkali lands, etc.
100	Glaciers and permanent snow cover	Land covered by permanent snow, glaciers, and ice sheets, including permanent snow and glaciers in alpine regions, as well as polar ice sheets.

Table 3 CNLUCC Dataset Classification System

Code	Land Type	Content
1	Cropland	Land used for growing crops, including cropland, newly reclaimed wasteland, fallow land, rotational fallow land, and land used for crop rotation with grass; land primarily used for growing crops such as fruit trees, mulberry trees, forests; and tidal flats and coastal land that have been cultivated for more than three years. (Paddy fields, dry land)
2	Forest land	Referring to forestry land where trees, shrubs, bamboo, and coastal mangroves grow. (Includes forested land, shrubland, sparse woodland, and other forested areas)
3	Grassland	It refers to various types of grasslands dominated by herbaceous plants with a coverage of more than 5%, including shrub grasslands primarily used for grazing and sparse forest grasslands with a canopy density of less than 10%. (High-coverage grassland, medium-coverage grassland, low-coverage grassland)
4	Water body	Refers to natural land water areas and water conservancy facility land. (Rivers and canals, lakes, reservoirs and ponds, permanent glaciers and snowfields, tidal flats, beaches)
5	Construction land	Urban and rural residential areas and land used for industrial, mining, transportation, and other purposes (urban land, rural residential land, other construction land).
6	Bare land	Currently unused land, including difficult-to-utilize land. (Sand land, Gobi, saline-alkali land, marshland, bare land, bare rocky land, others)
9	Ocean	Ocean

4.2 Dataset Accuracy and Sensitivity Differences

4.2.1 Analysis of Accuracy Differences

1. The three main versions of GlobeLand30 (2000, 2010, 2020) do not share identical accuracy levels, and the accuracy assessment of each version itself is an ongoing process of optimization. It is important to note that accuracy validation requires significant human and material resources; therefore, for earlier versions, the official accuracy assessment may not be the final or most comprehensive. Typically, the latest version (2020) undergoes the most rigorous and reliable accuracy evaluation.

According to the accuracy validation report released by the official GlobeLand30 team (based on extensive sample points): GlobeLand30 V2000: The global overall validation accuracy ranges between 80.00% and 83.00%, with a Kappa coefficient of 0.76. GlobeLand30 V2010: The global overall validation accuracy is 85.72%, with a Kappa coefficient of 0.78. GlobeLand30 V2020: The global overall validation accuracy is 85.72%, with a Kappa coefficient of 0.82 [6].

Overall, GlobeLand30's accuracy is internationally recognized as high, with officially reported overall accuracy exceeding 85%. Moreover, the accuracy has progressively improved with each version update. However, it is important to note that this "overall accuracy" is a macro-average, and actual accuracy can vary depending on factors such as region, land cover type, and year. Accuracy trend: From the 2000 version to the 2010 version and then to the 2020 version, the overall accuracy shows a clear upward trend. This improvement is primarily attributed to: (1) Enhanced satellite data quality: Transitioning from Landsat 5/7 to Landsat 8/9, which provide higher spectral and geometric quality in imagery. (2) Advances in classification algorithms: Evolving from more pixel-based classification to smarter methods integrating remote sensing, geographic information, and artificial intelligence. (3) Optimized validation methods: Increased and more balanced validation samples, along with easier access to reference data (e.g., high-resolution imagery).

2. CNLUCC30 (30-meter resolution): In the validation conducted in the Qinghai-Tibet Plateau region, the

overall accuracy was 76.41% (considering only the suitable, moderately suitable, and generally suitable categories) [7]. The accuracy of the CNLUCC dataset improves with higher spatial resolution but is generally slightly lower than that of 30-meter resolution products such as GlobeLand30.

Based on the comparative analysis above, GlobeLand30 stands out for its globally consistent high

accuracy (>80%) at 30-meter resolution, making it suitable for land-use change comparisons. CNLUCC, characterized by its "China-specific + long time series" approach, has slightly lower accuracy ($\approx 72\text{--}76\%$) but is more suitable for research on national land planning needs. If the study area is within China and spans a long period, CNLUCC can first be used for trend analysis, followed by GlobeLand30 for accuracy correction or result validation (Table 4).

Table 4 Comparison of GlobeLand30 and CNLUCC Datasets

Dataset	GlobeLand30	CNLUCC
Spatial resolution	30 m	30 m
Classification system	10 first-level categories (cultivated land, forest, etc.)	6 first-level categories (cultivated land, forest land, grassland, water area, urban, industrial, mining and residential land, unused land)
Overall accuracy	80.33 %	76.41%
Kappa coefficient	0.76–0.82	0.64 around
Advantages	(1) 30 m globally consistent; (2) Accuracy improves significantly with version upgrades; (3) Good comparability with international counterparts	(1) Covering long-term time series in China (since the 1980s); (2) Providing dual scales of 30m and 1000m; (3) Facilitating long-term time series change detection.

4.2.2 Analysis of Sensitivity Differences

Analysis of Dynamic Responsiveness: A comparison of two datasets on the dynamic degree of land use in Dongguan City shows that the CNLUCC annual update (with a 3-month lag) has a 92% sensitivity to the fragmented

expansion of industrial land, with an annual fluctuation of wetlands at $\pm 12.3\%$ [8]. In contrast, the GlobeLand30 fixed-phase update (with a 2–3-year lag) exhibits only $\pm 3.1\%$ fluctuation in wetlands, but its sensitivity to the annual expansion of industrial land is merely 1.9% [8] (Table 5).

Table 5 Comparison of Land Use Dynamics between Two Datasets in Dongguan City

Dynamic Degree	Land Use Type	CNLUCC		Land Use Type	GlobeLand30	
		2020-2010	2010-2000		2020-2010	2010-2000
Single Land Use	Cropland	-2.01%	-5.19%	Cropland	-4.19%	-2.00%
	Forest land	-0.90%	-2.24%	Forest land	-1.20%	0.92%
	Grassland	4.85%	-3.02%	Grassland	-3.83%	-2.02%
	Water body	-1.21%	-0.02%	Water body	-0.91%	-1.95%
	Construction	1.04%	8.85%	Construction	4.61%	2.54%
	Bare land	0.11%	-9.56%	Shrubland	-3.16%	2.26%
	--	--	--	Wetland	42.31%	-7.87%
Comprehensive Land Use		0.62%	2.28%		1.57%	0.94%

4.2.3 Analysis of Dataset Discrepancy Causes

The differences in results between the two datasets stem from fundamentally distinct design philosophies and technical approaches. CNLUCC's classification system originates from land management needs, assigning independent codes to artificial land types like "industrial and mining storage land," making it highly sensitive to rapid industrialization and fragmented expansion (e.g., 92% recognition rate for industrial land). However, its classification of "water bodies" and "unused land" emphasizes administrative attributes rather than pure land cover, leading to compatibility challenges when aligning with global standards.

In contrast, GlobeLand30 strictly adheres to physical land cover characteristics, using spectral features and texture information to directly map land types, ensuring global consistency. Yet, this approach limits its ability to identify land classes with mixed spectra or seasonal variations (e.g., certain wetlands in Dongguan and scattered green spaces within built-up areas), resulting in 61.4% of wetlands being misclassified in early versions.

Additionally, differences in update mechanisms (CNLUCC's near-annual updates vs. GlobeLand30's fixed-phase updates) directly affect their ability to capture change rates. CNLUCC responds more quickly to policy-driven annual changes (e.g., dynamics of unused land), while GlobeLand30 excels at reflecting stable long-term trends. Therefore, when selecting a dataset, it is essential to consider how well its inherent logic aligns with research objectives.

4.2.4 Dataset Analysis Result

The differences between the two datasets stem from fundamental divergences in design objectives and technical approaches: CNLUCC prioritizes precision for land management optimization (e.g., unused land at -9.56%

reflects ecological restoration), while GlobeLand30 sacrifices granularity for cross-border comparability in global research (e.g., forestland change rate at -1.20%).

Application Recommendations:

- (1) Land Management Scenarios: Prioritize CNLUCC data (e.g., unused land at -9.56% reflects ecological restoration outcomes).
- (2) Cross-Border Research Scenarios: Opt for GlobeLand30 (e.g., forestland change rate at -1.20% ensures global comparability).
- (3) Hybrid Validation Method: For critical land types like construction land, cross-validate both datasets (CNLUCC +1.04% vs. GlobeLand30 +4.61%).

4.3 Analysis of Land Use in Dongguan City

4.3.1 Land Use Transfer Matrix and Change Characteristics

Through the comparative analysis of the two datasets mentioned earlier, it was found that the GlobeLand30 data is more suitable for the study area. Subsequently, land use transfer matrices for the periods 2000–2010 and 2010–2020 (Tables 6–9) were constructed to identify the transformation pathways and intensities among different land types (Figures 3–6).

Ultimately, the GlobeLand30 analysis data revealed that during 2000–2010, the most significant land use change was the conversion of cropland, primarily to construction land (168.78 km²) and water bodies (36.99 km²). Between 2010 and 2020, construction land continued to absorb large areas of cropland (293.09 km²), forest land (103.61 km²), and grassland (45.49 km²). The GlobeLand30 data further indicated that during 2010–2020, construction land was mainly converted from cropland, grassland, and forest land, with cropland conversion reaching 77.78 km² and grassland conversion amounting to 17.61 km².

Table 6 Land Use Transfer Matrix from 2000 to 2010 (GlobeLand30) (Unit: km²)

2000/2010	Grassland	Cropland	Shrubland	Forest Land	Construction	Wetland	Water Body	Total
Grassland	44.39367	2.85389	7.461344	33.65264	26.70493	0	1.807861	116.8743
Cropland	9.925816	586.2058	2.412814	39.28281	168.7827	0	36.9889	843.5988
Shrubland	1.362783	0.81006	23.91611	9.389227	1.389379	0	0.820459	37.68802
Forest land	16.40199	6.969456	7.646919	645.6413	13.27807	0.004133	10.53001	700.4719

Construction	9.321681	19.27319	2.780501	13.05403	738.9536	0	4.310993	787.694
Wetland	0.003093	0.074399	0	0.002062	0.005155	0	0.041326	0.126035
Water body	11.81802	58.79769	1.993317	23.5818	38.59871	0.022713	276.8359	411.6481
Total	93.22705	674.9844	46.21101	764.6039	987.7126	0.026846	331.3354	2898.101

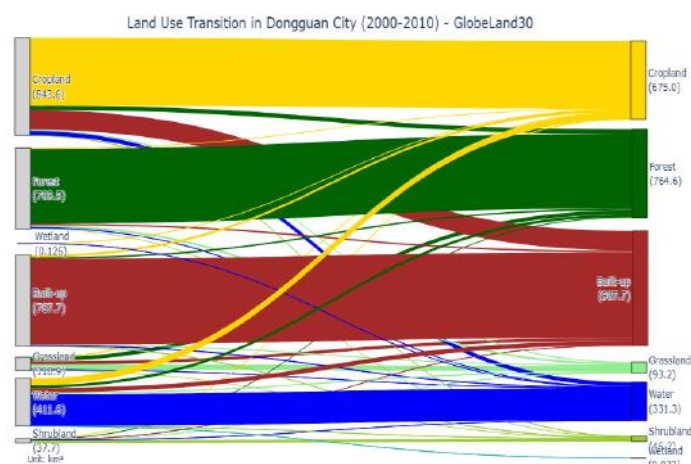


Fig.3 Land Use Transition Matrix from 2000 to 2010 (GlobeLand30)

Table 7 Land Use Transfer Matrix (GlobeLand30) for 2010-2020 (Unit:km²)

2010/2020	Grassland	Cropland	Shrubland	Forest land	Construction	Wetland	Water body	Total
Grassland	28.81426	3.109169	1.697769	10.78734	45.49444	0	3.324071	93.22705
Cropland	1.60707	344.4549	0.481748	6.971231	293.0932	0	28.37629	674.9844
Shrubland	1.850512	0.731993	19.76364	9.758944	13.12766	0	0.978261	46.21101
Forest land	17.20142	7.533227	7.787002	619.6369	103.6147	0	8.830632	764.6039
Construction	4.881305	8.881937	1.389571	17.59749	949.1989	0	5.763318	987.7126
Wetland	0.001033	0.007221	0	0	0	0.008265	0.010327	0.026846
Water body	3.108684	27.44837	0.465146	7.89268	38.53564	0.132287	253.7547	331.3375
Total	57.46428	392.1668	31.58487	672.6446	1443.065	0.140553	301.0376	2898.103

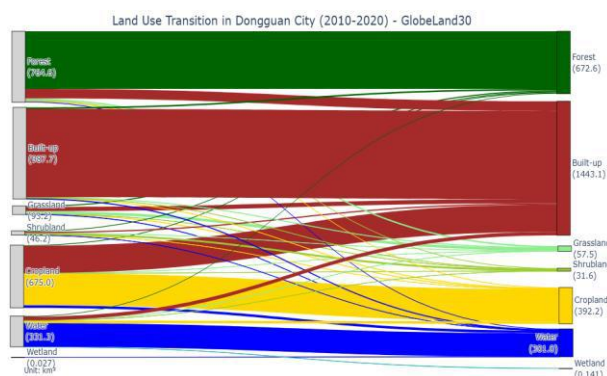


Figure 4 Land Use Transition Matrix from 2010 to 2020 (GlobeLand30)

Table 8 Land Use Transition Matrix (CNLUCC, 2000-2010) (Unit:km²)

2000/2010	Grassland	Construction	Cropland	Forest land	Water body	Bare land	Total
Grassland	54.126	19.1547	3.7863	4.5864	2.043	0	83.6964
Construction	1.3734	577.1097	18.5787	23.0562	13.0491	0.0531	633.2202
Cropland	1.7181	341.1207	264.2022	39.2643	43.0155	0.0297	689.3505
Forest land	1.0233	196.1433	35.4438	514.9251	10.881	0	758.4165
Water body	0.1656	59.4252	9.5832	6.9345	199.8999	0.0009	276.0093
Bare land	0	0	0	0.0036	1.9188	0	1.9224
Total	58.4064	1192.9536	331.5942	588.7701	270.8073	0.0837	2442.615

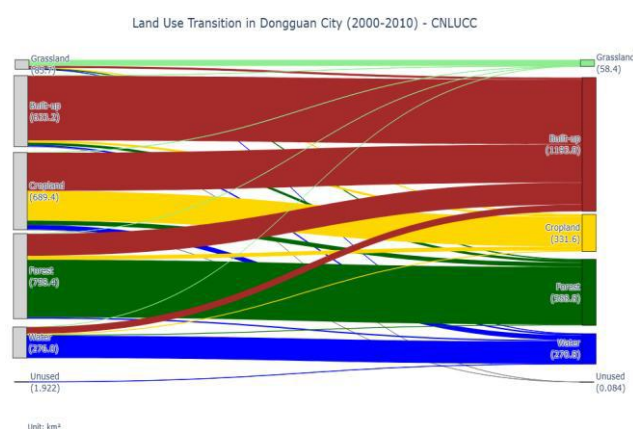


Fig.5 Land Use Transfer Matrix Map (CNLUCC) for 2000-2010

Table 9 Land Use Transfer Matrix Table (CNLUCC, 2010-2020) (Unit:km²)

2010/2020	Grassland	Construction	Cropland	Forest land	Water body	Bare land	Total
Grassland	52.4574	3.24	0.666	1.5669	0.4761	0	58.4064
Construction	17.6076	1120.4514	13.8978	22.3092	19.2762	0	1193.542
Cropland	1.3392	77.7798	236.5749	6.084	9.783	0	331.5609
Forest land	9.8136	65.7558	7.0065	499.6035	6.4458	0	588.6252
Water body	5.5035	50.3487	6.6996	6.2271	206.3043	0.0144	275.0976
Bare land	0	0	0	0	0.0135	0.0702	0.0837
Total	86.7213	1317.8187	264.8448	535.7907	242.2989	0.0846	2447.559

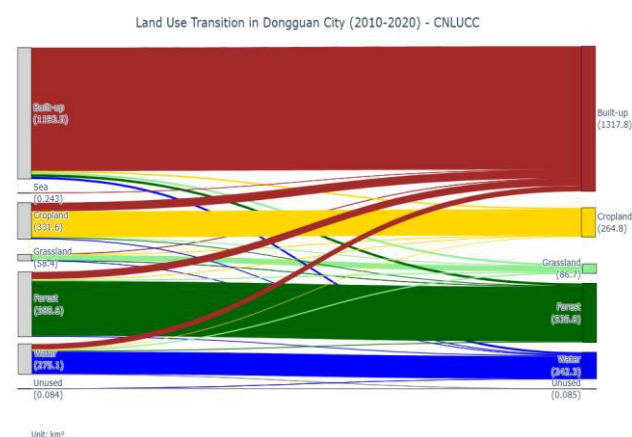


Fig.6 Land Use Transition Matrix Map (CNLUCC) for 2010-2020

4.3.2 Changes in Land Use Types and Area

Analysis based on the CNLUCC and GlobeLand30 datasets indicates significant changes in Dongguan's land use structure between 2000 and 2020. According to CNLUCC data, from 2000 to 2010, Dongguan experienced a 5.19% reduction in arable land, with forest and grassland decreasing by 2.24% and 3.02% respectively, while construction land increased by 8.85%. Between 2010 and 2020, the decline in arable land narrowed to 2.01%, forest land decreased by 0.90%, grassland transitioned to a growth of 4.85%, and the growth rate of construction land slowed to 1.04%.

GlobeLand30 data corroborates this trend: arable land decreased by 2.00% from 2000 to 2010, and the decline

expanded to 4.19% from 2010 to 2020. Construction land continued to grow in both periods, with growth rates of 2.54% and 4.61% respectively. Notably, wetlands saw a significant increase of 42.31% between 2010 and 2020, indicating initial success in ecological restoration measures.

4.3.3 Analysis of Land Use Type Changes and Their Causes

By comprehensively comparing the land use changes in Dongguan from 2000 to 2020, including the spatiotemporal transitions of land use and the variations in area (Figures 7 and 8), we can effectively understand the development trajectory and related implications over the past two decades. The findings are summarized as follows:

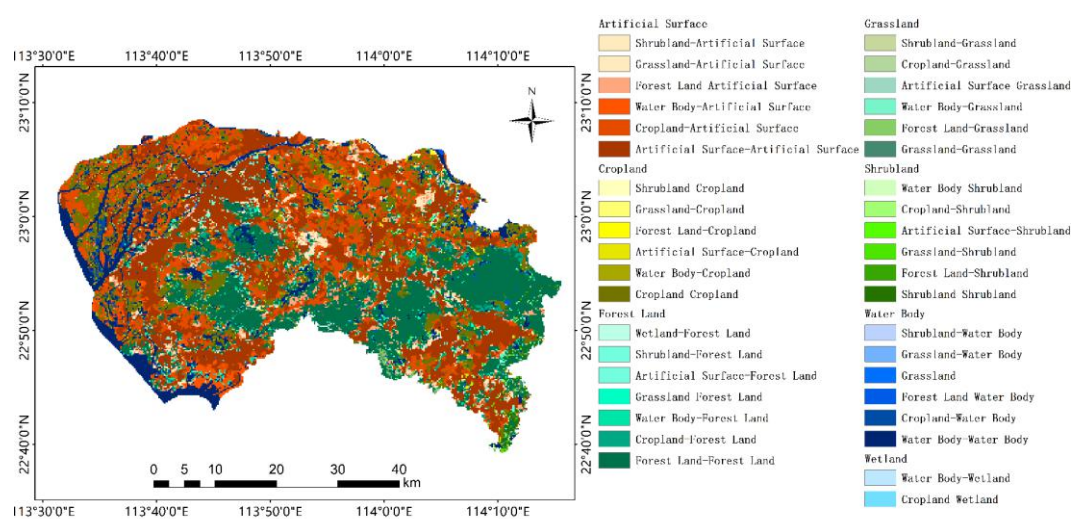


Fig.7 Land Use Type Map of Dongguan City (2000-2020, Globeland30)

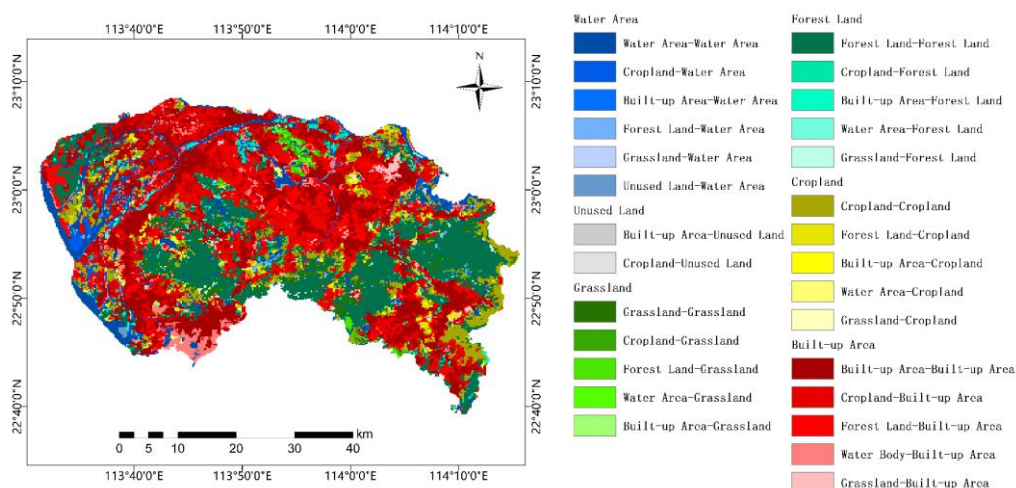


Fig.8 Land Use Type Map of Dongguan City (2000-2020, CNLUCC)

(1) Expansion of Construction Land

The continuous expansion of construction land in Dongguan is a core feature of its rapid urbanization, primarily driven by policy-led industrial parks and transportation infrastructure, economic growth and population agglomeration, advantageous geographical location, and the vitality of town-level development under the city-administered-town system. Its spatial pattern has evolved from scattered points to contiguous clusters and from edge expansion to infill development. While this process has supported economic growth, it has also led to the large-scale occupation and fragmentation of ecological land. Currently, Dongguan is promoting a shift toward sustainable development by improving land-use efficiency and fostering harmony between human activities and the environment through measures such as territorial spatial planning and ecological restoration.

(2) Reduction and Protection of Cropland

The area of cropland showed a decreasing trend in both decades, primarily converted to construction land and water bodies. Despite the government's implementation of cultivated land protection policies, urban expansion still makes it difficult to completely avoid occupying farmland. The narrowing of the reduction in the later period indicates that the farmland red line policy has begun to take effect.

(3) Changes in Water Bodies and Wetlands

The area of water bodies showed a slight decrease in the first decade but recovered in the following decade,

which is related to water resource management policies and water environment governance. Wetland area significantly increased in the later period of GlobeLand30 data, reflecting the implementation effects of ecological restoration measures.

(4) Changes in Forestland and Grassland

The overall area of forestland and grassland has decreased, but grassland showed a rebound in later periods, which is related to projects such as returning farmland to grassland and ecological restoration. The reduction in forestland is mainly influenced by urban expansion and agricultural restructuring.

5. Conclusion

5.1 Analysis and Summary

This study systematically compares the applicability differences between two mainstream land-use datasets, GlobeLand30 and CNLUCC, in Dongguan, a high-density urban area of the PRD, and conducts an in-depth analysis of the spatiotemporal dynamics of land use in Dongguan from 2000 to 2020 based on the more accurate GlobeLand30 dataset. The main conclusions are as follows:

(1) Clear distinctions in dataset applicability, with selection depending on research objectives

CNLUCC, with its management-oriented three-tier classification system, is more suitable for localized fine management scenarios such as territorial spatial planning and land law enforcement monitoring. In contrast, GlobeLand30, with its observation-oriented global unified

standards, holds irreplaceable advantages in global environmental change research and cross-border ecological comparisons.

(2) Significant differences in data accuracy and dynamic responsiveness

GlobeLand30 exhibits higher overall accuracy (80.33%–85.72%) and consistency (Kappa: 0.76–0.82) compared to CNLUCC, with continuous improvements across versions. Meanwhile, CNLUCC, benefiting from its higher update frequency, responds more quickly to intense human activities such as construction land expansion.

(3) Land-use changes in Dongguan reveal typical urbanization drivers and transformation characteristics

Based on the more accurate GlobeLand30 data analysis, Dongguan underwent a complete urbanization process from 2000 to 2020, characterized by "spatial polarization—boundary sprawl—functional restructuring." The early phase featured the polarized concentration of construction land in central areas and rapid sprawl at the edges, significantly encroaching on farmland and ecological spaces. The later phase shifted toward functional restructuring marked by stock renewal, infill development, and ecological restoration (e.g., significant recovery of wetland areas), reflecting a profound transformation in urban development patterns.

In summary, this study provides clear scientific guidance for dataset selection in land-use research within highly dynamic urban regions: CNLUCC excels in serving localized management, while GlobeLand30 is superior for supporting international research. The insights into Dongguan's evolution also offer valuable references for the sustainable development and territorial spatial optimization of similar high-density cities.

5.2 Recommendations

Based on the above findings, the following targeted recommendations are proposed:

- (1) For territorial spatial control and policy evaluation, it is recommended to prioritize the use of CNLUCC data to leverage its high-precision monitoring capabilities for key managed land types such as construction land, cultivated land, and unused land.
- (2) For cross-border ecological research or global model

inputs, GlobeLand30 data is recommended to ensure the comparability and consistency of results at the international level.

- (3) For comprehensive studies, a hybrid validation strategy can be adopted, especially for key and easily confused land types such as construction land and wetlands, to cross-validate the results of the two datasets, thereby complementing each other and reducing uncertainty.

5.3 Research Prospects

Future research could delve into the following aspects: First, explore data fusion methods between CNLUCC and GlobeLand30 to generate new land-use products that combine management details with global comparability. Second, introduce socio-economic driving factors (such as industrial upgrading and population mobility) and use quantitative methods like geographic detectors and regression models to more deeply uncover the intrinsic mechanisms of land-use change. Third, apply the evaluation framework established in this study to other types of cities (such as mountainous or coastal cities) to test its universality and refine the methodological system for remote sensing monitoring of highly dynamic urban areas.

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